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Implications of future climatic uncertainty on payments for forest ecosystem services: The case of the East Coast of New Zealand

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ABSTRACT

Forestry's long-term nature and associated uncertainties play against its consideration in land-use decisions. This study's objective was assessing the implications of uncertainty on the feasibility of afforesting erodible land with natives. The New Zealand example has global relevance enabling: innovative statistical representation of climatic uncertainty, economic uncertainty analysis due to existing payments for services, and the profitability of long-rotation species due to Māori's socio-cultural aspirations. We complemented a deterministic optimisation approach with Monte-Carlo methods to identify optimal afforestation areas representing uncertainty probabilistically. With stochastic dominance/efficiency tests, relevant to landowners, we identified that the uncertainty and profitability of long-rotation species increase at low discount rates, plausible due to low opportunity costs and inter-generational aspirations (not possible in competitive circumstances). At low discount rates, the high profitability odds of the long-rotation alternative compensate its high uncertainty and make it the preferred one even for highly risk-averse owners. With a probabilistic cost-benefit analysis, relevant to policymakers, we identified that the benefits necessary to cover erosion-reduction investments would need to be higher than expected to hedge against climatic uncertainty. These results were obtained through the uncertainty analysis. The methods/results covered in this study are relevant to land-use studies/models seeking to measure uncertainty impacts simply.

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1. Introduction

Forests provide some of the most valuable ecosystem services in the world, the other ecosystems being wetlands and rangelands (Costanza et al., 2014). An ambitious attempt made by Costanza et al. (2014) valued forest ecosystem services at $22 billion/year.[1] The importance of valuing these services stems from the need to acknowledge their economic contributions to society, hence fostering their preservation and expansion.

The measurement and valuation of these services has fostered the creation of policies that economically reward their generation (e.g. emission trading schemes). The creation of advanced measurement and valuation protocols and technologies (e.g. remote sensing and social media) has sparked the calibration of what used to be theoretical ecological and economic models to simulate the generation of ecosystem services as well as their demand (and valuation) temporally and spatially. However, these models rely on calibration processes that entail a certain degree of uncertainty, since they are based on sampled data, and use probability distribution functions (PDFs) to simulate properties about entire populations. Hence, the consideration of uncertainty in the modelling of ecosystem services is a critical extension to their early deterministic counterparts.

Monte Carlo methods popularised the probabilistic representation of uncertainty since the 1940s (Metropolis, 1987). Their early uptake contributed to their extensive use in various disciplines sparking the development of multiple specialised software

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[1] $ will represent New Zealand Dollars throughout the article. The going exchange rate at the moment of the development of the article was NZ$1.37/US$. Hence the original value assigned for forest ecosystem services was approximately US$16 billion/year.

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packages as well as routines in common programming languages. Their use in the specific context of decision-making under uncertainty have sparked the creation of various ranking tests that take as inputs the entire range of possible events in a variable's domain incorporating the human behavioural dimension (e.g. risk or loss aversion) (Hardaker, 2004). The application of these approaches in the area of ecosystem services has enabled the numerical and empirical assessment of the effects of risk aversion, for example, on the ranking and choice among various uncertain alternatives (Benítez et al., 2006; Goldstein et al., 2006; Djanibekov and Khamzina, 2016; Monge et al., 2016).

The advantage of the explicit consideration of uncertainty has been proven quite extensively in the land-use decision-making literature applied to ecosystem services. The development of spatial economic optimisation models mimicking decision-making has grown exponentially in the last couple of decades (Heckelei et al., 2012). The most commonly-used optimisation approach is mathematical programming due to its simplicity and tractability. Although uncertainty can be represented in these models to a certain extent (e.g. scenarios or quadratic programming), more complex approaches using heuristic methods have been developed to improve the shortcomings experienced with the former type of models (Musshoff and Hirschauer, 2009; Lehmann et al., 2013; Rabotyagov et al., 2014). However, the complexity of heuristics (e.g. search algorithms, non-convexities and stochastic processes) has precluded their use in large scale assessments (Doole and Pannell, 2008; Doole, 2015).

Hence, there is an opportunity to add value to widely-applied deterministic mathematical-programming methods by complementing their sets of deterministic results with widely-accepted Monte-Carlo simulation approaches and the economic theory developed to treat risk and uncertainty (e.g. stochastic dominance tests). The appeal of both approaches is their simplicity, tractability and wide use. Although there are far more comprehensive and complex methods, the benefit of using widely-accepted and relatively simple approaches would be to adequately use them to answer a specific question rather than developing complex models to answer these questions.

Although there have been several methods developed to cope with uncertainty in the ecological and economic disciplines, climate change poses an interesting opportunity to develop new ways to cope with biophysical uncertainty (e.g. ecosystem services) using economic theory. Empirical and process-based models (e.g. Rahmstorf (2007) and Keenan et al. (2011)), taking as inputs the results from complex Earth System Models (ESM) or General Circulation Models (GCM) (e.g. Scholze et al. (2006)), have helped to model biophysical relationships under future climatic uncertainty.

1.1. Case study area: East Coast of New Zealand

The current study took place in the East Coast region of the North island of New Zealand, namely the Waiapu catchment in the Gisborne district (Fig. 1). New Zealand as a whole and the specific region in question offer a relevant case study to the uncertainty literature for four major reasons: (1) Current GCMs and ESMs often poorly represent some physical processes in the region, (2) the East Coast is one of the most erosion-prone regions in the world, (3) the existence of two environmental policies rewarding regulating services from forests, and (4) the region's predominant Māori population and its implications for the preference of native forestry products with uncertain niche market circumstances. These four points are expanded upon below. Hence, the forest ecosystem services considered in this study are: product provisioning (e.g. timber and honey), carbon sequestration and avoided erosion under climate change.[2]

There is currently a National Science Challenge in New Zealand to properly model the climate processes in the Southern Ocean and Antarctica, namely the "Deep South" region.[3] The core objective of the Challenge is to assemble the first New Zealand ESM (NZESM) to properly model physical processes of atmospheric and oceanic circulation in the region. However, the relatively recent launch of the Challenge precludes the use of the potentially more refined results from the NZESM. Hence, this lack of data presents an opportunity to use sparse GCM-downscaled spatial data from previous projects (Tait et al. 2016a) and statistical techniques that do not require large datasets to fit a probability distribution function, namely the use of non-parametric empirical distribution functions.

The East Coast is one of the most erosion-prone regions of New Zealand and the world (Cumberland et al., 1980; Glade et al., 2006). This is the legacy of a massive land-use change phenomenon that started back in the 1880s when the first Europeans settled in the region and cleared most of the native forests for pastoral farming purposes. This drastic erosion vulnerability of the land has exerted negative effects on the productivity of rural land, its profitability and, hence, the economic growth of the region.

The region has the highest proportion (~45%) of the Māori ethnic group in New Zealand, with strong cultural, environmental and intergenerational aspirations (NZ Parliamentary Library, 2012). Furthermore, the tribal and permanent land ownership structures, the resulting lack of access to financial credit (i.e. no easily tradable collateral) and geological impediment of the land (i.e. steep slopes) make alternative investments other than forestry less appealing. Due to these aspirations and circumstances, forest systems consisting of native tree species that stabilise the soil with their root systems could turn out to be the most sustainable alternatives. Native species with the potential to contribute to productive planted forest systems analysed here are Mānuka (*Leptospermum scoparium*), Tōtara (*Podocarpus totara*) and Kawakawa (*Piper excelsum*). These species have been chosen for this study due to their high cultural significance and potential high profitability, which is conditioned on the uncertain niche markets where their products would be traded due to their uniqueness.

New Zealand provides an ideal location for this study due to the existence of environmental policies incentivising two important regulating services from forestry, namely climate change mitigation (i.e. carbon sequestration) and erosion control. The New Zealand Emissions Trading Scheme (NZ ETS) is a domestic policy implemented to meet the nation's international climate change obligations. Through the NZ ETS a price is assigned to a tonne of carbon dioxide equivalent (tCO_2e) sequestered, or a New Zealand Unit (NZU) (i.e. 1 tCO_2e = 1 NZU), creating an incentive to plant trees (Ministry for the Environment, 2017). The Erosion Control Funding Programme (ECFP) is a regional initiative, led by the Gisborne District Council and the Ministry for Primary Industries, granting landowners funding to control erosion on the worst eroding or erosion-prone land in the district. Eligible treatments include the establishment of indigenous forestry in retired grazing land (Ministry for Primary Industries, 2017b).

The uncertain benefits obtained from these policies, due to their design and the effects of climate change, have important implications for landowners and governments alike. Previous modifica-

[2] Forests provide other relevant ecosystem services that are not considered in this study such as biodiversity, recreation, tourism, etc.

[3] http://www.deepsouthchallenge.co.nz/

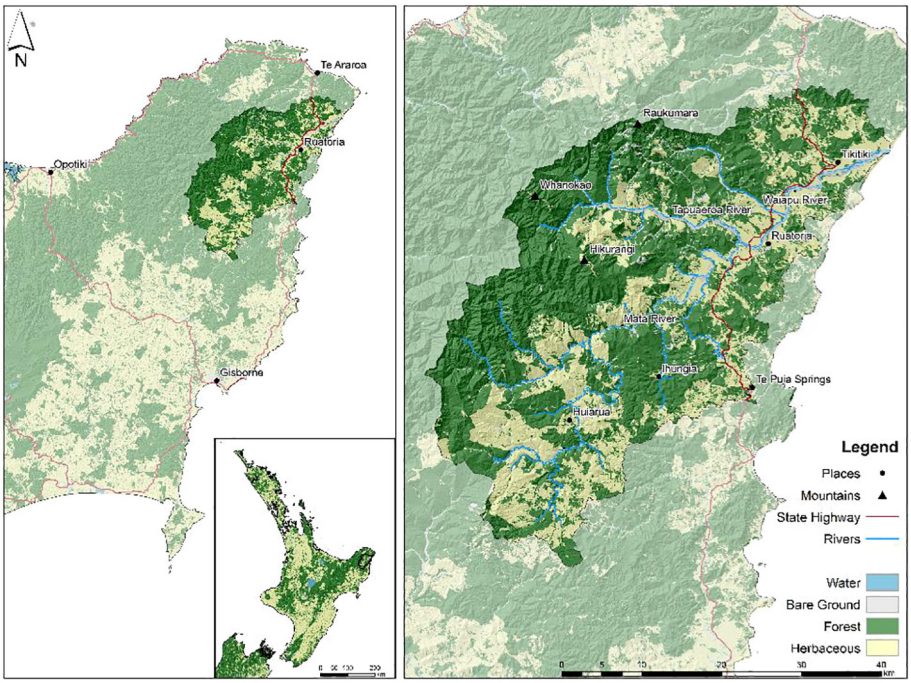

Fig. 1. Location of the Waiapu catchment in the North island of New Zealand.

tions of the NZ ETS resulted in highly uncertain carbon price signals that affected landowners' trust and, hence, enrolment numbers.[4] The ECFP has been designed as an incentive mechanism (i.e. early lump-sum payments) to promote land-use change as a means to control for erosion. However, due to the uncertain erosion forecasts under climate change, it would be worthwhile to assess the effectiveness of this policy in reaching the expected public benefits.

1.2. Objectives

The objective of this study was assessing the implications of various sources of uncertainty (e.g. markets, policies, ecosystem services and climate change) on the feasibility of afforesting erodible land, including payments for ecosystem services, using simple and replicable approaches. To achieve this objective and also demonstrate the value of uncertainty analysis:

1. We used two widely-accepted, complementary approaches:
   a. A *deterministic* economic optimisation model and
   b. A Monte-Carlo approach to represent uncertainty in a probabilistic manner;
2. We used simple parametric and non-parametric probability distributions to perform the Monte-Carlo simulations;
3. We used widely-accepted stochastic dominance and efficiency tests to rank uncertain afforestation options of various rotation lengths – relevant to landowners with various time and risk preferences;
4. We developed a simple probabilistic benefit-cost analysis to measure the downside uncertainty of public environmental investments – relevant to policymakers interested in the impacts of uncertain climatic change.

[4] A modification of the NZ ETS back in 2009 permitted the surrendering of international Kyoto carbon units and, due to an oversupply of international units coupled with a low demand from the EU, such modification resulted in a drastic NZU drop to a record low of $2/NZU in 2013 (Richter and Chambers, 2014).

The study is structured as follows: (1) description of the method and data sources used; (2) interpretation of results; and (3) conclusions and recommendations for further studies.

2. Materials and methods

2.1. Overall method

Fig. 2 summarises the overall method by graphically representing the linear flow of data (averages and distributions) and models used in the two complementary approaches: (1) the deterministic optimisation routine and (2) the post-optimisation uncertainty analysis. The detailed descriptions of the data sources, methods and models used are developed in the following sub-sections.

The optimisation routine, based on mathematical programming principles, identifies the optimal areas to be afforested subject to specific erosion-reduction goals and based on average profitability and erosion parameters per land use. The uncertainty analysis is performed by using the optimal afforested areas and the probability distribution functions (parametric and non-parametric) of key economic and biophysical parameters representing uncertainty.

The two final products from the uncertainty analysis are: (1) the stochastic dominance tests ranking individual afforestation options according to their uncertainty levels and the decision-makers' risk and time preferences, and (2) the probabilistic benefit-cost analysis measuring the downside uncertainty of public environmental investments and the additional benefits required to compensate this uncertainty.

It is worth mentioning that for simplicity and replicability's sake, the adopted method disregards the potential endogeneity between uncertain parameters and optimised results. For example, once the landowner has experienced the high price uncertainty offered by some afforestation alternatives, he/she could switch to another less risky alternative in the middle of the time horizon. The post-optimisation uncertainty analysis adopted in this study only considers the uncertainty experienced by the landowner once he/she has stuck to a specific option. The ideal, but more complex,

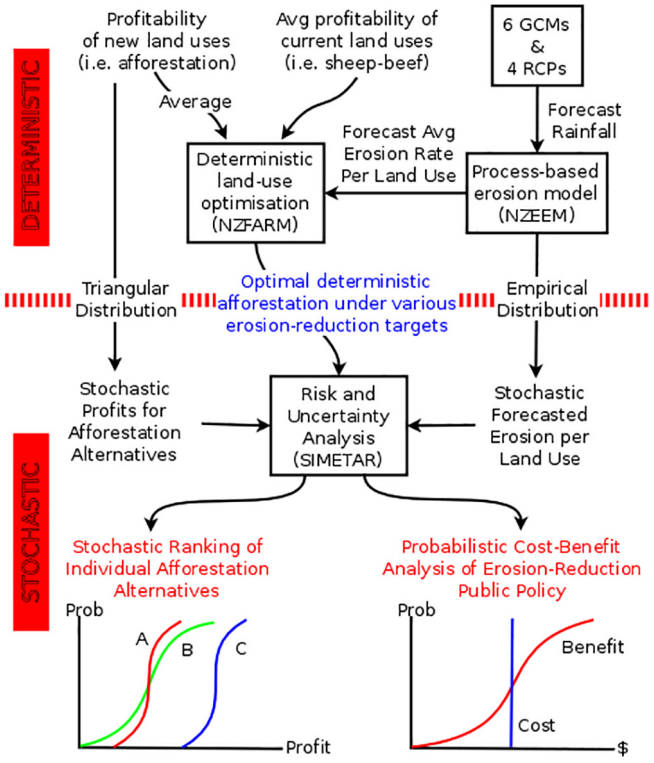

Fig. 2. Graphical representation of the flow of the coupled and complementary approaches.

methods to handle this endogeneity would be stochastic programming or robust optimisation.

2.2. Cash flows of afforestation scenarios

Since the establishment of indigenous forestry in retired grazing land is an eligible erosion treatment under the ECFP, three indigenous tree species were chosen through a set of consultations with community representatives, namely Mānuka, Tōtara and Kawakawa. Three continuous-cover forest management scenarios were designed for this analysis by combining the aforementioned tree species. Refer to Fig. 3 for a graphical representation of the transitions. All scenarios started with Mānuka, based on its potential to provide: (1) shelter for the establishment of Tōtara and Kawakawa, (2) early revenue from honey sales, (3) a thick canopy for rain interception and (4) a solid rooting system for erosion reduction. The afforestation scenarios are the following:

1. Mānuka only: Chosen as a resilient crop suitable for growing conditions on the East Coast of New Zealand, providing revenues from the sale of honey. Productivity was assumed to start at 10 kg/ha of honey from year 4, building up to 30 kg/ha from year 6, and reducing to 20 kg/ha from year 28 into perpetuity (ANZ Research, 2015).
2. Mānuka and Tōtara: Mānuka was used as a nurse crop providing shelter to aid in the establishment of Tōtara, using the latter as a long-term high-value alternative. Honey production from Mānuka was assumed to stop in year 21 due to shading as the canopy transitioned to Tōtara. Sustainable recoverable volumes were assumed to increase slowly over seven selective harvests each 10 years apart, starting at 100 m^3/ha in year 88 and finishing at 107 m^3/ha in year 148 (Bergin and Kimberley, 2003).
3. Mānuka, Tōtara and Kawakawa: Similar to the previous scenario with the addition of Kawakawa as a high-value understory crop. Kawakawa is of high cultural value, and produces a specialized product for use in pharmaceuticals. In this scenario it was assumed Kawakawa planting would start from year 25 after Tōtara canopy closure. Kawakawa harvesting was assumed to start one year after the first planting initially providing 100 kg of dried Kawakawa leaves per hectare, and increasing to 900 kg/ha by year 32 (Heaphy et al., 2013).

To assess the profitability of the three afforestation scenarios, a discounted cash flow approach was used. Operational costs were calculated in line with common practices of radiata pine plantations in New Zealand – assuming high hindrance from slope and understory. In scenarios where multiple operations occurred within the same year, an adjustment factor was used to avoid double counting the cost of time spent accessing trees. The range in prices assumed for the various products are listed in Table 1. The variability of these prices was specified based on the best information available in the literature. For more details on the assumptions for costs, productivities and silvicultural practices, please refer to the first section of the Supplementary Material.

2.3. Spatial optimization

A spatially-explicit economic optimisation model was used to contrast the *deterministic* profitability of native tree species with that of the predominant land use in the region (i.e. sheep-beef) enabling the identification of the areas that would need to be afforested (i.e. erosion hotspots) under various *deterministic* future erosion-reduction goals. The model used was the New Zealand Forest and Agriculture Regional Model (NZFARM), a widely used non-linear, partial equilibrium mathematical programming model of New Zealand land use that is spatially delineated at the farm-parcel level (Daigneault et al., 2016). The model has been parameterised to assess how changes in climatic conditions, technology, market drivers, resource constraints, or environmental policies will affect a host of economic or environmental performance indicators that are important to decision-makers and rural landowners (Daigneault and Samarasinghe, 2015; Daigneault et al. 2017; Fernandez and Daigneault, 2017). For a more detailed description of the model's mathematical formulation and calibration procedure, please refer to the second section of the Supplementary Material.

A highly simplified version of the model was used for this study to quantify and track changes in land cover and soil erosion, which was then used to estimate impacts on a wider range of ecosystem services. For replicating this type of analysis, any linear (or non-linear) programming model that maximises overall profits across land uses in a specific region, considers area allocation among land uses as the main decision variables, and a constraint equation tracking erosion rates per land use and limiting total erosion in the region could be used as a substitute for the version of NZFARM used for this study (e.g. Doole, 2015).

For the specific case of the Waiapu catchment, baseline land use and enterprise areas are based on a GIS-based land use map created in 2014 using the latest information from Agribase and the NZ Land Cover Database version 4 (LCDBv4).[5] Production yields, stocking rates, input costs, and output prices for sheep-beef farms come primarily from the literature (Newsome et al., 2008; Lincoln University, 2013; Ministry for Primary Industries, 2013b,a), and have been verified with agricultural consultants and enterprise experts.

[5] Available at https://www.asurequality.com/our-solutions/agribase/ and https://lris.scinfo.org.nz/layer/412-lcdb-v40-land-coverdatabase-version-40/5

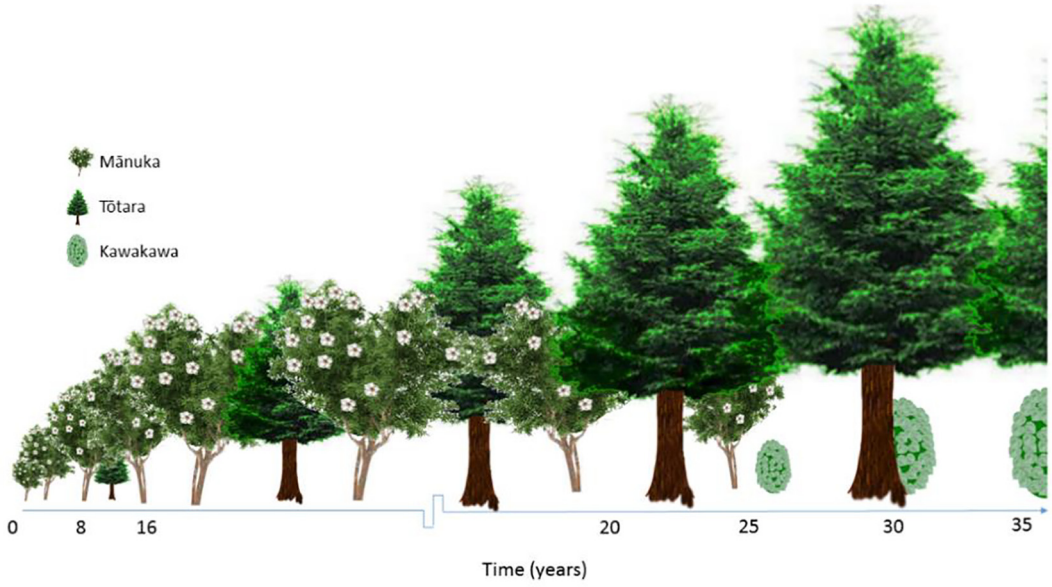

Fig. 3. Afforestation transitions through time.

Table 1
Parameters for triangular distributions to represent uncertainty for the profitability of the native tree species used as afforestation options.

Uncertainty type	Parameter	Unit	Uncertainty in% μ	Expected β	Minimum β*(1-μ)	Maximum β*(1+μ)
	Mānuka price	$/kg honey	10	35	31.5	38.5
Market	Tōtara price	$/$m^3$ timber	40	350	210	490
	Kawakawa price	$/kg dry leaves	40	110	66	154
Policy	Carbon price	$/$tCO_2e$	50	17	8.5	25.5
Ecosyst. Service	Carbon sequest.	tCO_2e/ha/yr		7.6	7	9.2

Erosion and soil loss figures are based on methods from Ausseil et al. (2013), and based on the New Zealand Empirical Erosion Model (NZEEM) (Dymond et al., 2010).

2.4. Sources of profitability uncertainty

Since the optimisation exercise was of a deterministic nature, a simple and replicable Monte-Carlo approach was used as a complement to represent probabilistically the uncertainty expected from various sources. As previously mentioned, there are various specialised software packages (e.g. @Risk, Crystal Ball, SIMETAR, etc.) and routines in popular programming languages (R, Python, Matlab, GAMS, etc.) that can perform these Monte-Carlo simulations. The stochastic modelling process is explained below to encourage others replicate these procedures in their preferred tools.

Various sources of uncertainty (e.g. policy, market and climate change) have been considered that will affect the impact of the generation of ecosystem services on landowners' and policymakers' decision-making processes. The following sections list the uncertain parameters considered with their respective data and methods. Table 1 lists the parameters considered for the various sources of uncertainty.

2.4.1. Market uncertainty

The forest products considered (e.g. Mānuka honey, Tōtara timber and Kawakawa dry leaves for pharmaceuticals) are for niche markets where there is a high demand uncertainty. Due to the novel nature of these products, there is no significant price time series to use to calibrate a parametric distribution (e.g. normal). Hence, for practical purposes the uncertainty around expected prices was modelled using a symmetric triangular distribution where the uncertainty is expressed as a percentage (μ) around the mean (β) as shown Fig. 4. The uncertainty (μ) is relative to the level of market development for the niche product and is based on price ranges obtained from literature (Heaphy et al., 2013; Steward et al., 2014; ANZ Research, 2015).

2.4.2. Policy uncertainty

The carbon price signal created by the NZ ETS has been so erratic in the last 5 years due to the relatively young market and policy changes. Because of this high uncertainty there is no sensible way to calibrate any existing price series to a parametric distribution.

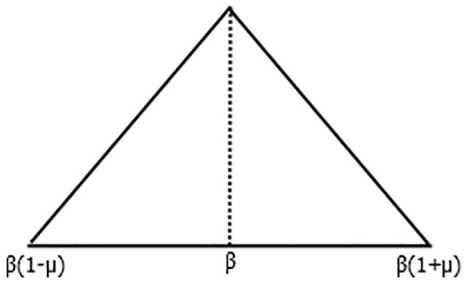

Fig. 4. Triangular distribution function with respective parameters.

Hence, a symmetric triangular distribution was also adopted where uncertainty is expressed as a percentage around an expected price of \$17/tCO_2e, which is the current price, and an uncertainty factor of 50% resulting in a minimum and a maximum price of \$8.5/tCO_2e and \$25.5/tCO_2e, respectively. The resulting minimum and maximum reflect historically recent price ranges observed after NZ ETS policy modifications (Funk et al., 2014; CommTrade, 2017).

2.4.3. Carbon sequestration uncertainty

The expected sequestration rate is defined by a set of lookup tables that the Ministry for Primary Industries in New Zealand has developed. These tables were developed from areas dominated by regenerated Mānuka/Kānuka, representing about 70% of the total area in New Zealand regenerated with native species (Ministry for Primary Industries, 2017a).[6] Trotter et al. (2005) defined a national carbon sequestration range for Mānuka and Kānuka, which was used to define the minimum and maximum sequestration rates for an asymmetric triangular distribution (last row of Table 1). Although carbon sequestration was modelled for a 150-year time horizon, the uncertainty was based on the average annual sequestration rates for a 40-year timespan.

2.4.4. Profitability uncertainty

All of the previous sources of uncertainty (except for climate change) were encapsulated in the following profitability measures for the three afforestation scenarios:

$$\tilde{\pi}_s = \sum_{t}^{150} \sum_{d} \frac{(\tilde{p}_{t,s,d} * q_{t,s,d}) + (\tilde{y}_{t,s} * \tilde{z}_{t,s}) + ECFP_{r \in t} - \varphi_{t,s}}{(1+i)^t} \quad (1)$$

where the $\sim$ sign identifies stochastic variables, s the afforestation alternatives, d the multiple products from each afforestation alternative, t represents every year of the 150-year time horizon, r is a subset of time including the periods when the ECFP payments take place[7], π represents the net present value (NPV), p is the product price (e.g. Mānuka honey, Tōtara timber and Kawakawa dry leaves), q is the quantity of the product, y is the price of carbon, z is the annual carbon sequestration rate, φ represents costs, i is the private discount rate, and *ECFP* the payments granted by the government to control for erosion.

2.5. Erosion under uncertain climate change

Climate change uncertainty was modelled with empirical distributions using baseline erosion rates developed with the New Zealand Empirical Erosion Model (NZEEM) developed by Dymond et al. (2010). In this study, we estimated annual erosion for all 286 sheep-beef land parcels in the catchment and a combination of 6 GCMs for the 4 Representative Concentration Pathways (RCP) scenarios for year 2100.[8] Refer to the third section in Supplementary Material for more information. The entire dataset included a total of 6,864 baseline erosion forecasts (6 GCMs × 4 RCPs × 286 parcels) represented by erosion coefficients (taking 2012 as the base or equal to 1) for year 2100. Fig. 5 shows catchment maps of the baseline annual erosion rates per parcel for 2015 and 2100. Using 286 sets of 24 forecasted erosion coefficients, 286 non-parametric empirical distributions were developed for each sheep-beef parcel in the catchment following the procedure developed in Richardson et al. (2000) and used in Monge et al. (2016) in the following manner:[9,10,11]

1. The means ($\bar{x}$) were first estimated using the 24 NZEEM erosion coefficients (ec) for the various land parcels:

$$\bar{x}_{l,t} = \frac{\sum_{c}^{24} ec_{c,l}}{N} \quad \text{for t} = 89 \text{ or year } 2100 \quad (2)$$

where c represents the set of 24 observations obtained from 6 GCMs and 4 RCPs for year 2100, t time, l the 286 sheep-beef parcels in the catchment, and N is the total number of observations (i.e. 24).

2. Percent deviates (dev) from the mean were then estimated using:

$$dev_{c,l,t} = \frac{ec_{c,l,t} - \bar{x}_{l,t}}{\bar{x}_{l,t}}, \forall c, l \quad \text{and } t = 89 \quad (3)$$

3. Sorted the percent deviates from minimum to maximum using a sorting function ($sort$):

$$sortdev_{c,l,t} = sort(dev_{c,l,t}), \forall l \quad \text{and } t = 89 \quad (4)$$

4. Developed probabilities for the sorted deviates ($sortdev$):

$$\begin{aligned} &P(Pmin) = 0.0, \text{ where } Pmin = Min(sortdev_{c,l,t}) * 1.0001 \\ &P(sortdev_{1,l,t}) = (1/N) \cdot 0.5 \\ &P(sortdev_{2,l,t}) = (1/\text{N}) + P(sortdev_{1,l,t}) \\ &\vdots \\ &P(sortdev_{N,l,t}) = (1/\text{N}) + P(sortdev_{N-1,l,t}) \\ &P(Pmax) = 1.0, \text{ where } Pmax = Max(sortdev_{c,l,t}) * 1.0001 \end{aligned} \quad (5)$$

where *Pmin* and *Pmax* are pseudo-minimum and pseudo-maximum values close enough to the observed extremes by a factor of 1.0001.[12]

5. Uncertainty through time was modelled through a combination of: (1) an empirical function using the sorted deviates and probabilities developed in the previous steps, (2) a linear trend as the mean between the base erosion differential in 2012 (=1)

[6] Forest owners have two options to quantify changes in carbon stocks: the default lookup tables and the field measurement approach. The former is used for participants with less than 100 hectares of post-1989 forest land in the NZ ETS and is based on default lookup tables publicly available and published by the government. The latter is used for participants with more than 100 hectares who need tailored growth curves for their specific blocks to minimise under- or over-reporting carbon stocks. We have used the lookup tables for practical purposes.

[7] ECFP payments have been assumed to take effect in three instalments: First 50% in t = 0, an additional 30% in t = 1, and the final 20% in t = 5. The total undiscounted payment sums up to \$1,500/ha.

[8] The 6 best-performing GCMs for the New Zealand region were selected, based on comparisons with observations over the historical data period of the models, namely the HadGEM2-ES (UK), CESM1-CAM5 (USA), NorESM1-M (Norway), GFDL-CM3 (USA), GISS-E2-R (USA) and BCC–CSM1.1 (China) (Tait et al., 2016b).

[9] The main benefit of using an empirical distribution function is that it relies on as few assumptions as possible about the data. Contrary to parametric distributions where a large number of observations are necessary to identify optimal parameters through maximum likelihood or method of moment approaches, an empirical distribution function can be generated with a small dataset.

[10] Similar to Scholze et al. (2006), our analysis did not assign probabilities to scenarios or weights to models but, instead, we created an empirical distribution using the outcomes (i.e. erosion baselines).

[11] Most software packages or programming languages used to model stochastic processes offer functions to develop empirical distribution functions such as *ecdf* in R and Matlab among others.

[12] In a standard empirical distribution the probabilities of simulating the observed minimum and maximum are zero. Hence, the inclusion of the pseudo-minimum and pseudo-maximum is to cause the simulated distribution to return the observed extreme values.

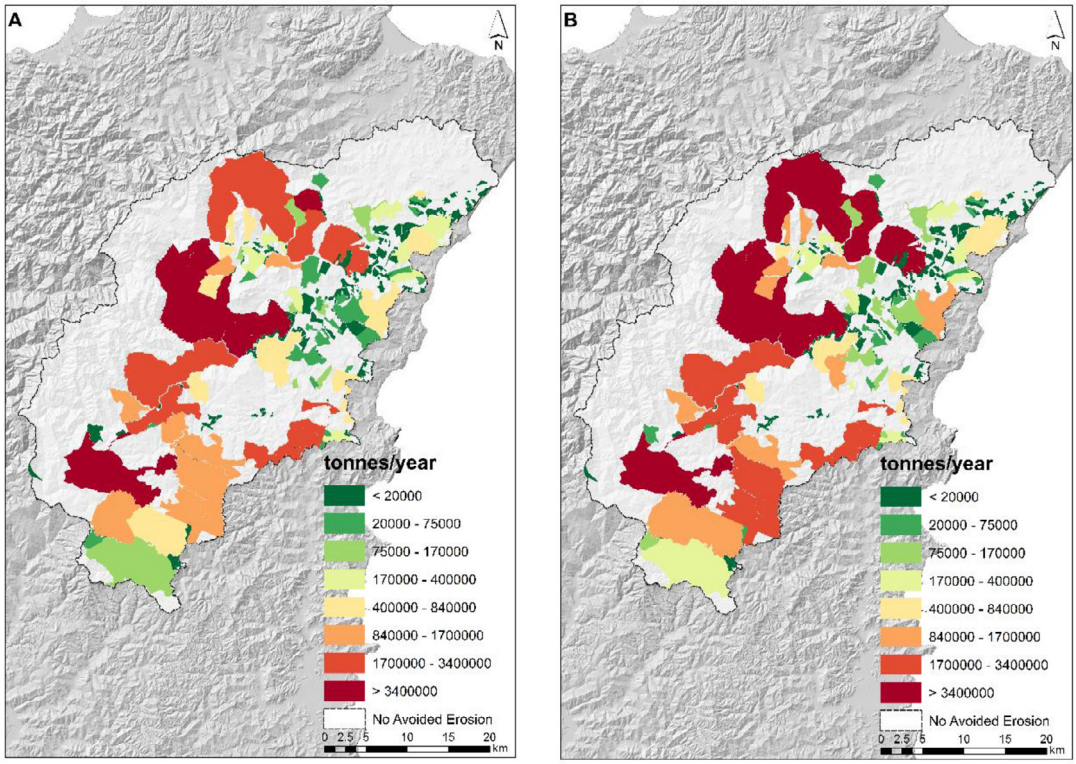

Fig. 5. Total baseline erosion from sheep-beef parcels in the Waiapu catchment: (A) modelled erosion in year 2015 and (B) forecasted erosion in year 2100 using the average of a suite of 6 global circulation models and 4 representative concentration pathways.

and the 2100 mean developed in the first step, and (3) an increasing expansion factor to model increasing uncertainty in the following manner:

$$\widetilde{ec}_{l,t} = \bar{x}_{l,t} * [1 + (\widetilde{dev}_{c,l,t} * ef_t)] \quad (6)$$

$$\widetilde{dev}_{c,l,t} = EMP(sortdev_{c,l,t}, P(sortdev_{c,l,t}, Pmin, Pmax), \widetilde{usd}_t) \quad (7)$$

where ef_t is an uncertainty expansion factor that increases linearly from 0 in 2012 to 1 in 2100, *usd* is a uniform standard deviate generated for each time period, and *EMP* represents the empirical distribution function. When $ef = 1$, we would obtain the same coefficient of variation estimated from the original 24 climate-change erosion estimates for 2100. When $ef = 0$, we would obtain the mean. Notice that *usd* is the same across *l* or, in other words, there is a perfect stochastic spatial correlation. The latter assumption implies that the direction and, to a certain extent, the magnitude of the erosion effects will be the same across parcels in a specific year. However, the magnitude will still change per parcel as each parcel contains its respective deviations from its respective mean.

6. Finally, the stochastic erosion estimates for sheep-beef ($\widetilde{erosion}^{s\&b}_{l,t}$) were estimated based on the baseline erosion estimates in 2012 ($erosion^{s\&b}_{l,t=1}$) as follows:

$$\widetilde{erosion}^{s\&b}_{l,t} = erosion^{s\&b}_{l,t=1} * \widetilde{ec}_{l,t} \quad (8)$$

2.6. Stochastic dominance to rank afforestation scenarios

Various stochastic dominance tests were used to rank the afforestation alternatives. These are outlined in detail with the purpose of giving readers plenty of options to be implemented in their preferred packages. Since the various tests are based on comparing the cumulative distributions functions (CDF) of the afforestation scenarios, 500 Monte-Carlo simulations were first performed for each scenario to obtain the CDFs for the NPV variables.[13] The results would allow land owners and managers to compare afforestation options.

The tests used in this study were: first degree dominance (FDD), second degree dominance (SDD), Stochastic Dominance with Respect to a Function (SDRF) and Stochastic Efficiency with Respect to a Function (SERF). The first two (FDD and SDD) are widely available tests in various software packages (e.g. R, Matlab, @Risk, SIMETAR, etc.) and rely on a small set of assumptions about the decision-maker's utility function.[14] The last two are only available in SIMETAR to the best of our knowledge, rely on a larger set of assumptions and identify tipping points (i.e. thresholds) across a range of risk aversion coefficients.[15] Denoting the cumulative distribution functions (CDF) of the NPVs of the Mānuka-only (MO) and Mānuka-Tōtara (MT) scenarios as $f(\pi)$ and $g(\pi)$, respectively, then MO would dominate MT:

- By FDD if the CDF of the MO scenario is entirely to the right of the CDF of the MT scenario or $f(\pi) - g(\pi) \geqslant 0 \forall \pi$
- By SDD if the CDF of both alternatives cross each other and the CDF of the MT scenario is a mean-preserving spread of the MO scenario or $\int_{-\infty}^{\pi} [f(\pi) - g(\pi)] d\pi \geqslant 0 \forall \pi$

[13] The simulations and stochastic dominance tests were performed with the Excel Add-in SIMETAR (Richardson et al., 2008). The simulations were performed using the Latin Hypercube sampling method (McKay et al., 1979) and the Mersenne Twister random number generator (Matsumoto and Nishimura, 1998).

[14] FDD assumes that all decision makers are non-satiated (i.e. non-decreasing utility function) (Hadar and Russell, 1969). SDD additionally assumes that all decision makers are risk averse.

[15] SDRF ranks alternatives for decision makers whose utility functions are defined by a lower and upper risk aversion coefficients (Meyer, 1977). SERF relies on a utility function specification (Hardaker et al., 2004).

- By SDRF if the MO scenario is the dominant alternative for the two limiting cases represented by a lower (r_1) and upper (r_2) risk aversion coefficient or $\int_{r_1}^{r_2}[f(\pi)-g(\pi)]U'(\pi)d\pi \geqslant 0 \forall \pi$
- By SERF if the certainty equivalent of the MO scenario (CE_{MO}) is higher than the one from the MT (CE_{MT}) scenario or $CE_{MO} > CE_{MT}$ evaluated at a specific risk aversion coefficient.[16]

The stochastic dominance tests were performed under various discount rates ranging from 1 to 5%. In addition to using values close to the market rate for forest investments (Row et al., 1981; Klemperer et al., 1994), we explore the option of using lower values closer to the historical social discount rate (Gollier and Hammitt, 2014), which can potentially make long-rotation options (e.g. Tōtara) more preferable than alternatives. In this specific case involving a Māori community with long time-horizons, low discount rates could also be justified on the grounds that investments in afforestation are made: in permanently-owned land by the community (i.e. non marketable) with geographical impediments for high-return options (i.e. steep slopes), and to maximize both long-run economic and social welfare. That is, planting native species is for the community's inter-generational benefit, including non-market values such as cultural significance.[17] The theoretical grounds to justify low discount rates to assess investments affecting generations to come has been a topic of discussion among several prominent economists (Weitzman, 1998; Arrow et al., 2013; Knoke et al., 2017). In this paper, the purpose of the sensitivity analysis is more descriptive, rather than prescriptive, to show the interactions between uncertainty and discount rates.

2.7. Probabilistic cost-benefit analysis of ECFP under uncertain climate change

Using the forecasted erosion estimates under uncertain climate change, a simple probabilistic cost-benefit analysis was developed to help policymakers determine the efficiency of the ECFP in reaching the expected public benefits under an uncertain future.

For this, NZFARM was used to evaluate the impact of imposing a wide range of erosion reduction targets. Since 90% of the total erosion in 2015 was from sheep-beef farms (i.e. ~46 million tonnes/year), NZFARM identified the optimal area of sheep-beef farms to afforest based on a deterministic cost-effective erosion control. The three afforestation scenarios, and respective expected NPVs, were used as potential land-use options.

The following formulas were used to represent stochastic benefits, fixed ECFP payments and perform the probabilistic cost-benefit analysis. Since the ECFP is a fixed per-hectare payment, the total cost of achieving the various erosion-reduction goals was estimated with the second term of the right-hand side expression of the following formula. The value of the benefits (pe) were modelled as unitary annual benefits or $ per tonne of avoided erosion per year as shown in the first term of the right-hand side expression in the following formula.[18]

$$\widetilde{Benefit}_e - Cost_e = \left[\sum_{l}^{286}\sum_{t}^{89}\frac{\tilde{\tau}_{l,t} * pe_{t,e}}{(1+j)^t} * ha_{l,e}\right] - \left[\sum_{l}^{286}\sum_{r\in t}\frac{ECFP_r}{(1+j)^r} * ha_{l,e}\right] \quad (9)$$

where t represents time for a forecasted horizon of 89 until year 2100, l represents the 286 sheep-beef parcels in the catchment, e the erosion-reduction goals, τ is the avoided erosion (in tonnes/ha/yr), j the public discount rate of 2%, pe is the value attached to avoided erosion (in $/tonne/yr), and ha are the afforested hectares identified by NZFARM under various erosion-reduction goals.

Avoided erosion (τ) was modelled as a fixed 90% reduction from the stochastic baseline erosion ($erosion^{s\&b}$) achieved through afforestation as suggested by Dymond et al. (2006) and Marden (2012) and as shown in the following formula.

$$\tilde{\tau}_{l,t} = \widetilde{erosion}^{s\&b}_{l,t} * 0.90 \quad (10)$$

Due to the stochastic nature of the benefits, the following formula shows a probabilistic representation of the cost-benefit analysis. The key output variable would be the probabilities of obtaining a benefit-cost ratio greater or equal to 1.

$$Prob(\widetilde{Benefit}_e \geqslant Cost_e) = Prob\left(\frac{\widetilde{Benefit}_e}{Cost_e} \geqslant 1\right) \quad (11)$$

The ultimate purpose of the probabilistic cost-benefit analysis is to identify the "threshold public benefit" or the public benefit that would need to be achieved to compensate the government's investment in the ECFP (i.e. benefit-cost ratio greater than 1) under various levels of certainty considering uncertain avoided erosion under climate change. Hence, for a risk-averse decision maker, it is expected that this threshold benefit will need to be higher as the levels of certainty increase to compensate for the probabilities of underestimating (i.e. low-tail or downside uncertainty) avoided erosion.

Assuming that the discounted threshold benefits (in $/tonne) are represented by ρ for the different erosion-reduction goals (e), the aim is to identify the levels of the threshold benefit that would result in greater odds of obtaining a benefit-cost ratio higher or equal to 1:

$$\rho_e = \sum_{t}^{89}\frac{pe_{t,e}}{(1+j)^t} \quad (12)$$

$$\rho_e \overset{?}{\Rightarrow} Prob\left(\frac{Benefit_e}{Cost_e} > 1\right) = 50\%, 75\% \& 100\% \quad (13)$$

3. Results

3.1. Spatial optimisation and forecasted uncertain erosion under climate change

The Waiapu catchment has a land area of approximately 161,000 hectares, comprised mainly of sheep-beef farming (54%), plantation forestry (25%) and native bush (19%). The modelled baseline estimate of total net revenue is $20.4 million/yr, which equates to about $126/ha/yr. The majority of net revenue is earned from plantation forestry (83%), followed by sheep-beef (11%) and horticulture and arable cropping (5%). The fact that a high proportion of revenue is earned through forestry on a relatively small area of land suggests that landowners in the catchment may need additional incentives or technical assistance to improve or change their land use. The 2015 baseline soil erosion is estimated to be 51.1 million tonnes/yr, or 316 tonnes/ha/yr, which is one of the highest

[16] The certainty equivalent is the minimum fixed monetary payment that an individual would be willing to accept to be indifferent between forgoing or accepting an uncertain alternative.

[17] The structure of Māori businesses differs from a conventional one (e.g. sole trader or company) since they involve large groups of stakeholders defined by family or tribal relationships.

[18] This was done to contrast the results from this study to other national or regional studies that have tried to value avoided erosion in New Zealand.

average erosion rates in New Zealand and in the world (Cumberland et al., 1980). The 2100 baseline erosion under climate change for all farms is estimated to be 72.6 million tonnes/yr, of which more than 90% is estimated to be sourced from sheep-beef farms, i.e. 65.8 million tonnes/yr.

Forecasted erosion and avoided erosion for each reduction scenario are listed in Table 2. Notice that avoided erosion for the catchment only happens in sheep-beef farms due to afforestation. The total afforested areas in sheep-beef farms are listed in the last column of Table 2. Notice that the afforested area increases as the reduction target increases. The spatial location of these afforested areas is shown in Fig. 6.

As previously mentioned, to model uncertainty around the deterministic erosion forecasts listed in Table 2, we assumed a linear increment in mean forecasted erosion and an expanding uncertainty across time for the 286 sheep-beef farms. The summation of this forecast with its respective uncertainty is shown in Fig. 7A. The expanding uncertainty was based on an empirical distribution fitted with erosion forecasts for all 286 sheep-beef farms for year 2100. Fig. 7B shows a graphical approximation of the empirical dis-

Table 2
Forecasted erosion, avoided erosion and afforestation under various erosion-reduction scenarios in the Waiapu Catchment for all land uses and sheep-beef farms (S-B) only.

Reduction scenarios	Erosion (million t/yr)		Avoided erosion (million t/yr)		Change from 2100 baseline (%)		Afforested S-B area (ha)
	All	S-B	All	S-B	All	S-B	
2015-Baseline	51.1	46.1	N/A	N/A	−30%	−30%	N/A
2100-Baseline	72.6	65.8	N/A	N/A	0%	0%	N/A
2100-Low	45.9	39.2	26.6	26.6	−40%	−37%	16,704
2100-Medium	35.7	28.9	36.8	36.8	−56%	−51%	27,699
2100-High	25.5	18.7	47.0	47.0	−71%	−65%	41,875

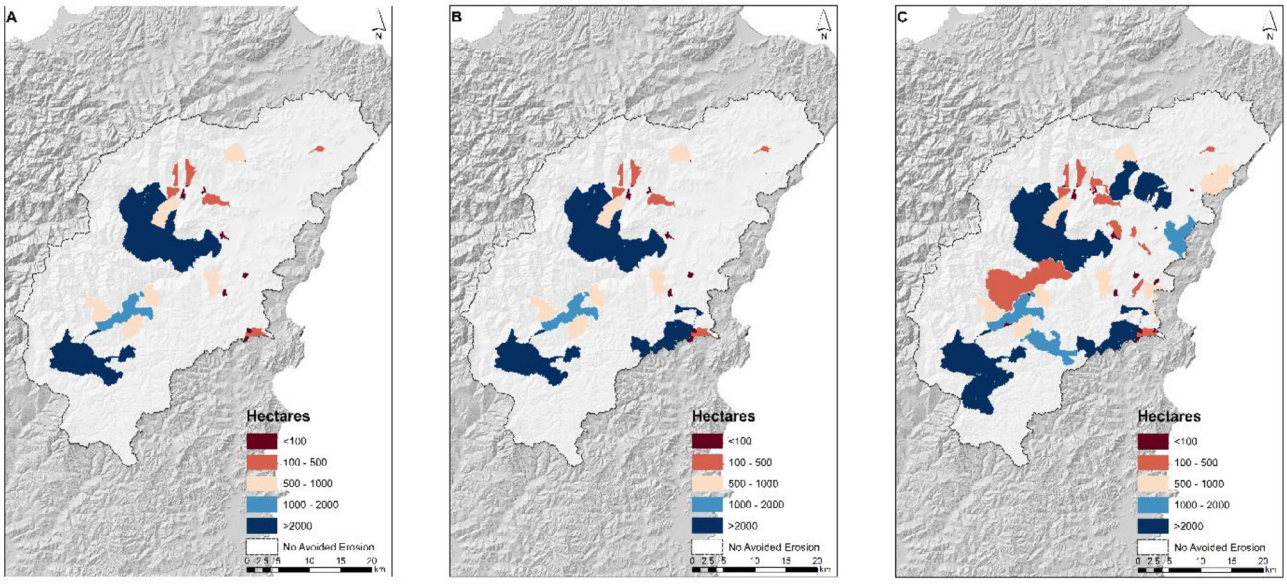

Fig. 6. Afforested areas of each parcel needed to reach various erosion-reduction goals identified with NZFARM: (A) low, (B) medium, and (C) high.

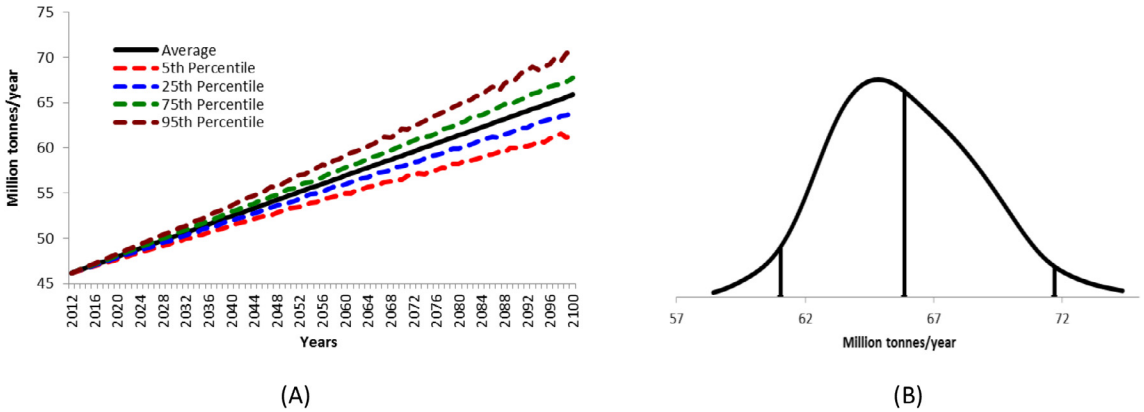

Fig. 7. Uncertainty around forecasted total erosion in sheep-beef farms in the Waiapu catchment under climate change: (A) through time and (B) in year 2100.

Table 3
Average NPVs and standard deviations for the three afforestation scenarios ($/ha).

Afforestation scenarios	Average	Std. dev. under various uncertainty sources (uncertain parameter)			
		Market (product prices)	Policy (carbon price)	Ecosys. service (carbon seq.)	All combined
MO	11,521	103	430	22	445
MT	−15,076	139	430	22	461
MTK	−120,844	11,304	429	35	11,276

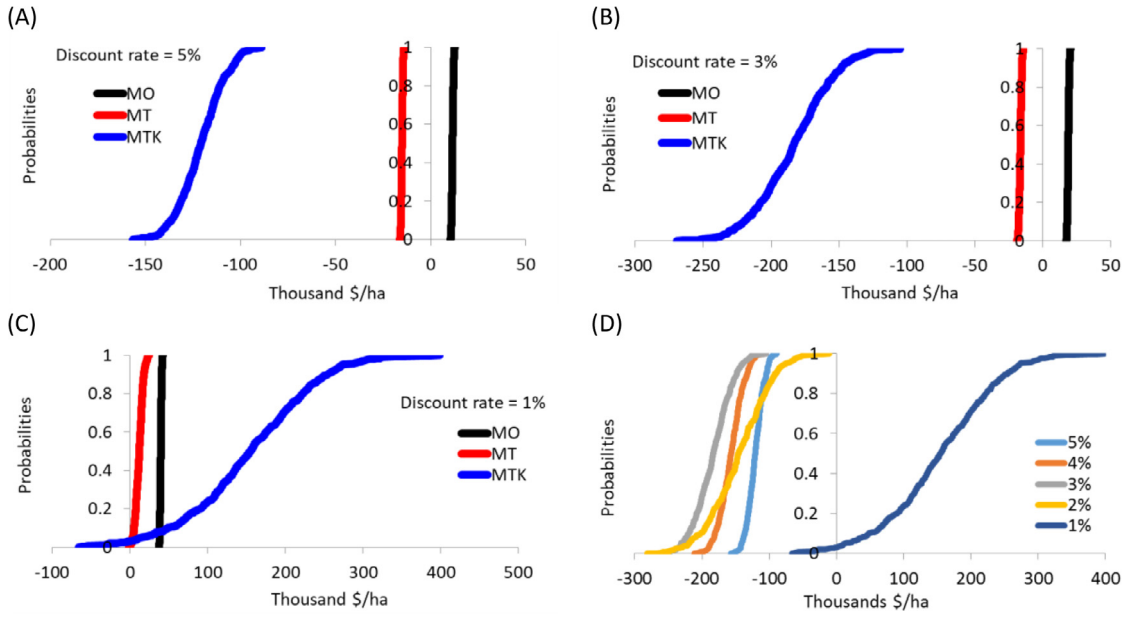

Fig. 8. Cumulative distributions functions of the net present values of the following afforestation scenarios: (A) all under a 5% discount rate, (B) all under a 3% discount rate, (C) all under a 1% discount rate, and (D) the mtk scenario under various discount rates.

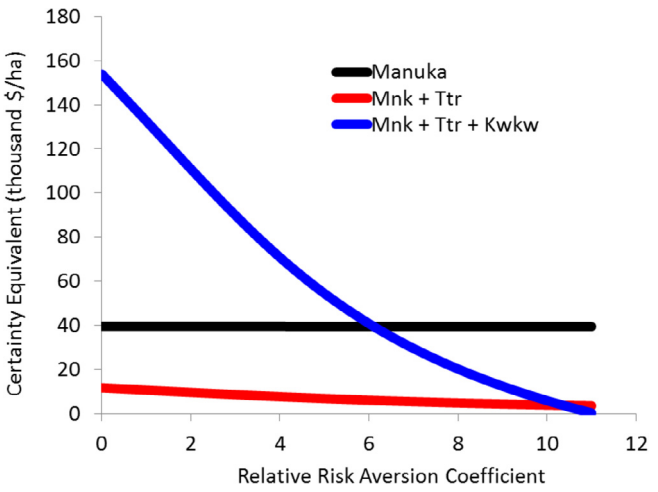

Fig. 9. Stochastic efficiency with respect to a function under a negative exponential function for the net present value of three different afforestation scenarios and a 1% discount rate.

tribution of total forecasted erosion in year 2100 generated by summing the 21 forecasts for all sheep-beef farms.

3.2. Stochastic dominance analysis

Table 3 lists the average NPVs and respective standard deviations for the three afforestation scenarios. The highest expected NPV is for Mānuka-only (MO), due to the early revenues from honey sales, followed by Mānuka-Tōtara (MT) and Mānuka-Tōtar a-Kawakawa (MTK). The most uncertain alternative is MTK followed by MT and MO (last column of Table 3). The standard deviations have been generated under various sources of uncertainty to identify the most relevant source for each scenario. Market uncertainty (i.e. product prices) is the most prevalent one for MTK whereas policy uncertainty (i.e. NZU price through NZ ETS) is the most relevant one for MO and MT.

Fig. 8 shows the CDFs of the afforestation scenarios under various discount rates. There are three important aspects to note about the CDFs from the graphs: (1) the width (i.e. uncertainty), (2) the position relative to the vertical axis cutting the horizontal one through 0, and (3) the position relative to the other CDFs. For example, the MTK option is the most uncertain one followed by MT and MO as previously identified. The uncertainty of the various options also increases as the discount rate decreases, which is expected since one of the sources of uncertainty are product prices, which in some cases would be received far in the future, being discounted less. This discounted uncertainty effect is more evident in Fig. 8D for MTK.[19]

The position relative to the vertical axis reflects profitability as the vertical axis represents an NPV = 0. Hence, the MO option is always to the right of the vertical axis meaning that its NPV is

[19] An additional insight from Fig. 8D is that the expected NPV decreases (i.e. moves to the left) when increasing the discount rate from 1% to 3% (i.e. early costs outweigh future revenues) and then increases asymptotically towards zero (i.e. moves closer to the vertical axis) when the discount rate is greater than 3% (i.e. costs still outweigh revenues but less so since they are heavily discounted).

Table 4
Total afforested areas and ECFP payments by erosion reduction scenario.

Reduction scenarios	ECFP payments ($/ha)		Afforested area (ha)	Total ECFP payments ($)
	Undiscounted	Discounted*		
2100-Baseline	1,500	1,463	0	0
2100-Low	1,500	1,463	16,704	24,436,176
2100-Medium	1,500	1,463	27,699	40,520,779
2100-High	1,500	1,463	41,875	61,259,442

* Discounted at a public discount rate of 2%.

greater than 0 in all three scenarios. The MT and MTK options become profitable under a discount rate of 1%. The probabilities of an NPV lower than 0 can also be identified by looking at the level at which the CDF cuts the vertical axis. Hence, the probabilities of an NPV lower than 0 for MTK and MT are quite low under a 1% discount rate.

Regarding the relative position of each CDF, the MO option is the preferred one by FDD since it is the one positioned farthest to the right in the first two cases – 5% and 3% discount rates in Fig. 8A and B, respectively. The CDFs under a 1% discount rate cannot be ranked by FDD nor by SDD since they cross each other and they are not mean-preserving spreads of one another, respectively. Hence, SDRF and SERF were used to rank them.

The rankings change when using SDRF and two extreme risk aversion coefficients representing a risk neutral (r_1=0) and an extremely risk averse landowner (r_2). The rankings are the following ones under the two extremes:

- Risk neutral landowner: MTK > MO > MT;
- Extremely risk averse landowner: MO ∼ MT ∼ MTK or indifferent among the three options.

SERF was used to graphically identify the risk aversion coefficient at which the rankings change. Assuming a negative exponential function and a 1% discount rate, the landowner would have to be exaggeratedly risk averse to prefer the MO and MT scenarios over the MTK one as shown in Fig. 9.[20] According to the risk aversion range developed by Anderson and Dillon (1992), an individual with a relative risk aversion coefficient of 4 is considered highly risk averse. As depicted in Fig. 9, the landowner would have to be extremely risk averse (i.e. relative risk aversion coefficient of 6) to prefer MO over MTK. The certainty equivalent of the MTK scenario drops quite drastically across the risk aversion range considered due to its high uncertainty. At relative risk aversion coefficients lower than 6, the risk premium that would have to be paid to the landowner to choose the MO over the MTK scenario would be the vertical difference between the MO's and the MTK's certainty equivalent lines. Hence, as the landowner type leans more towards risk neutrality (i.e. towards the left of the horizontal axis), the higher the risk premium has to be (∼$110 thousand/ha).

3.3. Probabilistic cost-benefit analysis

Table 4 shows the total afforested areas by scenario with respective total ECFP payments. The discounted ECFP payment was approximately $1,463 per hectare. Fig. 10 shows the CDF of the stochastic benefits under the low erosion-reduction goal contrasted against the total ECFP payments paid to the approximately

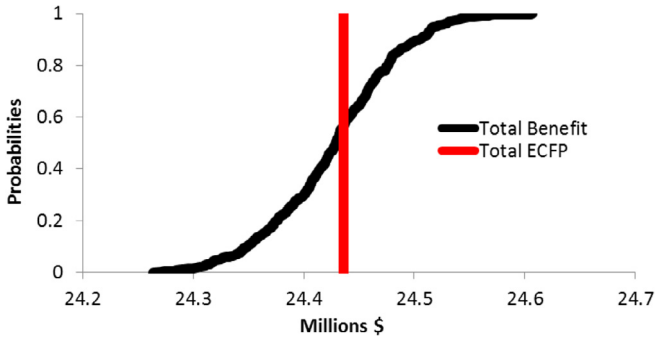

Fig. 10. Cumulative distribution function of the discounted public benefits obtained from a low erosion-reduction scenario and respective ECFP investment (i.e. cost).

17 thousand afforested hectares in the catchment. Important to notice that there is approximately a 50% chance that the ECFP will not reach the benefits desired due to climatic uncertainty, i.e. the benefit-cost ratio will be lower than 1.

Hence, to increase the odds of obtaining a benefit-cost ratio greater or equal to 1, the total benefits would need to be much greater than what the ECFP is paying. An important question worth answering would be, what would be the benefits that achieve greater odds that the benefit-cost ratio will be greater or equal to 1?

Fig. 11 shows the average discounted benefits (unitary and total) necessary to obtain a benefit-cost ratio greater or equal to 1 with various certainty levels for the different reduction scenarios. From a deterministic perspective, Fig. 11D shows that average unitary benefits would need to be approximately $1.14, $1.37, and $1.60/tonne of erosion to compensate ECFP investment half of the time (i.e. 50% certainty) for the low, medium and high reduction scenarios, respectively. However, to be almost 100% certain that the benefits will compensate the ECFP investment, the unitary benefits would need to increase to $1.15, $1.38, and $1.61/tonne for the low, medium and high reduction scenarios, respectively. This implies that total benefits would need to increase by approximately $0.2, $0.3, and $0.4 million, to almost certainly compensate total ECFP investment for the low, medium and high reduction scenarios, respectively.[21]

The estimation of benefits from avoided erosion can be performed in multiple ways from non-market valuation approaches to estimating the avoided investment in expensive technologies (e.g. water treatment). An example of the former is the study by Rivas Palma (2008), who estimated the benefit of avoiding erosion by forests at $105/ha/yr for the Hawke's Bay region in New Zealand, which is not directly comparable with the results obtained in this study. An example of the estimation of benefits from avoided costs is the study by Dymond et al. (2012) who performed

[20] According to Hardaker (2006), a utility function assuming constant relative risk aversion (e.g. power function) is more appropriate when wealth accumulation across time is a critical factor. However, wealth accumulation is not critical in this study since the cash flow approach used only considers annual surpluses (or losses). Hence, the negative exponential utility function assuming constant absolute risk aversion is good enough for the objectives sought.

[21] Estimated with the difference between total ECFP payments and the value that achieves 100% certainty on the second vertical axis in the various graphs.

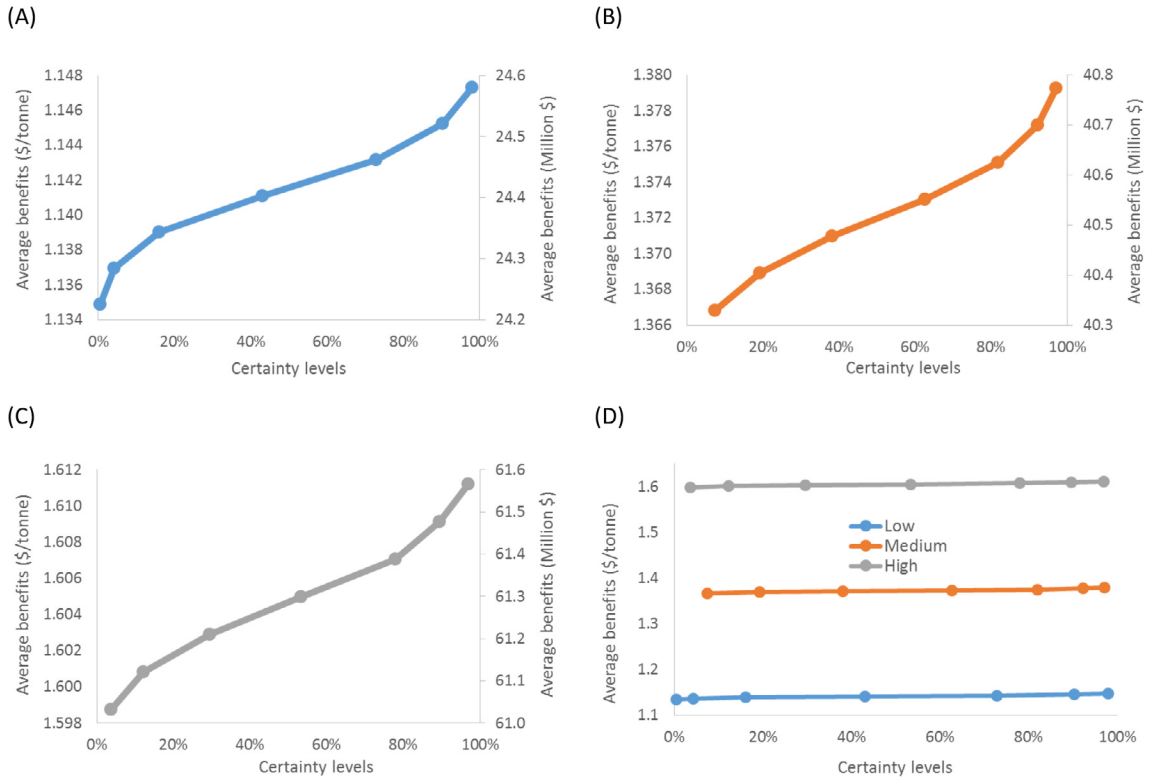

Fig. 11. The expected benefits from avoided erosion necessary to compensate ECFP investment with various certainty levels under climate change uncertainty for the following scenarios: (A) low, (B) medium, (C) high, (D) all reduction scenarios.

a national assessment using the total cost estimated in Krausse et al. (2001) and the annual estimate of eroded soil by Dymond et al. (2010), to arrive at a cost of $1/tonne, which is more in line with the results obtained in this study.

4. Conclusions and recommendations

We used NZFARM as a deterministic economic optimisation model to estimate the potential impact of climate change on erosion and to spatially identify the optimal areas to be afforested to achieve various erosion-reduction goals. Using 24 climate projections that vary by GCM and RCP, we estimated that if current land use practices continue, mean aggregate erosion could increase by 41% by the end of the century. These potential impacts coupled with an already extremely high erosion rate has driven national and local agencies to consider policy options and incentives to reduce erosion and their impacts to the economy and ecosystem, namely afforestation programmes. As a result, we estimated the area of existing sheep-beef pasture land that would have to be afforested to achieve various erosion-reduction levels in the catchment. Our analysis found that between 16,700 and 41,900 hectares of pasture would have to be afforested to achieve these reduction targets, equivalent to 19–48% of the current area of sheep-beef farms in the catchment.

Due to the deterministic nature of NZFARM, we used simple Monte-Carlo procedures as a complement to simulate the uncertainty stemming from various sources, namely market, policy, ecosystem service generation and climate change. For simplicity's sake, one of the caveats from performing the Monte-Carlo simulation as a post-optimisation exercise is the disregard of potential endogeneities between the uncertain parameters and optimised variables. Due to the lack of detailed historical or forecasted time-series data, we used simple and practical functions (i.e. triangular and empirical) that can be implemented in various software packages or programming languages. The triangular distribution was used to simulate the uncertainty around the profitability of various afforestation scenarios based on native tree species. The empirical distribution was used to add uncertainty around the expected erosion projections developed by NZEEM and NZFARM using the 24 climate projections for 286 sheep-beef farms in the catchment.

We used simple and widely-accepted stochastic dominance/efficiency tests to help landowners assess the implications of uncertainty on the profitability of afforestation options under various time and risk preferences. The short-rotation scenario (i.e. Mānuka-only) provided the highest return under more common market circumstances (i.e. competitive with high discount rates) due to the early revenues from honey sales, and was particularly appealing for risk-averse landowners. The scenario with the longest rotation (i.e. Mānuka-Tōtara-Kawakawa), being the most uncertain one, became the preferred alternative only under a very low discount rate (~1%) since the relatively high revenues obtained far in the future would not be as heavily penalised through time. Although the uncertainty from this scenario also increased as the discount rate decreased (reflecting the trade-off between profitability and uncertainty), the high profitability odds made it the preferred one even for highly risk-averse landowners. These results are of specific relevance to afforestation projects undertaken in regions were the landowners have strong cultural preferences for species with niche and uncertain markets, collective decision-making protocols, perpetual land-ownership, inter-generational aspirations and policies enabling payments for ecosystem services.

The simple probabilistic cost-benefit analysis was developed by combining the optimal afforestation areas identified by NZFARM with the probabilistic erosion forecasts. We identified, first of all, that the expected benefits from avoided erosion would need to increase as the erosion-reduction levels increase. We also identified that for each reduction level, the benefits would have to

increase even further to lower the chances of underinvesting in ECFP (i.e. increase the chances of a benefit-cost ratio greater or equal to 1). This result should incentivise the Ministry for Primary Industries and the Gisborne District Council to properly measure the likely benefits from the currently proposed ECFP budget specifically for the Waiapu catchment. These results are of specific relevance to policymakers with interests in considering climate-change uncertainty in public environmental investments.

Previous studies have estimated that the national impact from erosion and sedimentation is approximately $1/tonne (Dymond et al., 2012). According to our results, if the government relied on these national estimates as the unitary benefits from avoiding further erosion, then the ECFP investment would not be worthwhile in the Waiapu catchment – not even under our low reduction scenario. However, due to the peculiar circumstances of the catchment, a study should be performed to properly measure the benefits expected from avoiding erosion. We recommend that the study should include climate change projections to account for low-tail or downside uncertainty. The study should not only consider the proximate benefits such as avoiding investments in expensive technologies, among others, but also the social impacts on the community as well as the impacts on the various ecosystems that are affected by erosion and sedimentation (e.g. freshwater and marine ecosystems). A proper estimation of the benefits in the catchment would not only support investing in specific expected reduction levels but also in identifying the likelihood of a successful investment under climate change uncertainty.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecoser.2018.04.010.

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